

Research on the Coupling Mechanism between Personalized Education and Intelligent Multidimensional Teaching Quality Evaluation Based on AI Large Models

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Abstract: Addressing the deep-seated structural contradiction between "large-scale education and personalized cultivation of top-notch innovative talents" amidst the continuous expansion of postgraduate education, and the existing bottlenecks in traditional postgraduate education such as a single evaluation dimension, lagging process feedback, and the separation of teaching and evaluation, this paper, based on educational theory and system mechanism design, constructs a personalized education theoretical model and an intelligent multidimensional teaching quality assessment theoretical model based on an AI-powered large-scale model. The personalized education theoretical model, by integrating multimodal data such as visual, audio, and text, establishes a six-dimensional quantitative indicator system covering behavioral patterns, academic progress, interest matching, learning progress, knowledge point mastery, and behavioral relevance. The intelligent multidimensional teaching quality assessment theoretical model, centered on three levels—"basic course quality, teaching behavior, and interactive feedback"—designs a multidimensional quantitative indicator system including blackboard writing standardization, lesson plan quality, semantic differences in abstracts, temporal behavioral transformation, and genuine teacher-student emotions. Based on this, this paper studies the two-way dynamic coupling mechanism between personalized education and multidimensional teaching quality assessment, proposes a multi-level support framework covering cloud service layer, AI large model layer, AI-driven functional service layer, data processing layer and platform system layer, and designs in depth the implementation path and institutional guarantee mechanism for advanced training, providing solid theoretical model support and systematic mechanism design for resolving the contradiction between large-scale postgraduate education and personalized training.

Keywords: Artificial Intelligence Education Model; Postgraduate Education; Personalized Training; Multidimensional Teaching Quality Assessment.

1. Introduction

In recent years, with the continuous and substantial expansion of postgraduate enrollment in China, the cultivation of high-level talents in higher education has entered a new stage of development [1, 2]. However, postgraduate students vary greatly in their professional backgrounds, undergraduate training models, and existing research directions. With the expansion of the training scale, "homogenization, standardization, and one-size-fits-all" training under the traditional education model have been magnified many times over. The cultivation of high-level, top-notch innovative talents faces a deep structural contradiction between large-scale coverage and personalized development [3].

Both "China's Education Modernization 2035" and the "New Generation Artificial Intelligence Development Plan" explicitly emphasize the need to leverage modern information technology to accelerate the transformation of talent cultivation models, organically combining large-scale education with personalized training, and constructing a new "AI + Education" ecosystem based on educational application scenarios [4]. In the context of postgraduate education, top-tier innovative talents lies in their ability to explore complex and unknown academic innovations, their ability to transfer interdisciplinary thinking, and their ability to tackle practical engineering challenges. This attribute determines that each postgraduate student exhibits significant individual

heterogeneity in terms of knowledge reserves, research interests, cognitive construction pace, and problem-solving paths. However, traditional teaching practices have long been constrained by a single evaluation dimension, insufficient personalized support, and a disconnect between teaching and evaluation [5].

The recent technological breakthroughs of large AI models (such as ChatGPT, DeepSeek, Doubao, Wenxinyiyan) provide foundational models that can be further fine-tuned. Leveraging their capabilities including deep semantic understanding, cross-modal reasoning and generation (the synergy of vision, speech and text), and autonomous agent workflow orchestration, these models open up a brand-new path for theoretical construction to address dilemmas in the education sector [6]. In this paper, closely aligned with the goals of postgraduate education reform, delves into the theoretical design of a personalized postgraduate education model and an intelligent multi-dimensional teaching quality assessment model based on large-scale educational models and multi-modal technologies. It elucidates the efficient coupling mechanism of their bidirectional dynamic empowerment and establishes a multi-level support framework and institutional guarantee mechanism encompassing five core functional layers.

2. Overall Content Architecture Design

2.1. Characteristics of the Large-Scale Artificial Intelligence Education Model

Based on cutting-edge academic definitions, the EdGPT (Generative Education-specialized Transformer) is not simply a general-purpose model applied to the education field [7]. Rather, it is a professional intelligent system built upon a general-purpose foundational model, integrating a high-quality vertical corpus of education data (covering textbooks, courseware, subject knowledge graphs, student learning logs, supervisory evaluation standards, and real-world teaching behavior sequences) for supervised fine-tuning (SFT), intent alignment, and retrieval-augmented generation (RAG) [8]. Designed for high-standard postgraduate training scenarios, the EdGPT possesses four key characteristics:

1. Professionalism and High Fault Tolerance Requirements for Application Scenarios: Graduate courses involve advanced professional knowledge and complex cutting-edge theories. Large-scale models must accurately understand the logic and mathematical formulas of the discipline, and combine vector knowledge base retrieval under RAG to effectively eliminate factual "illusions" and ensure the academic rigor of the output content.

2. Value Compliance and Ideological Security of Content Generation: Graduate education shoulders the fundamental mission of cultivating morality and talent. The system must establish a strict warning word defense and algorithm content security review mechanism to ensure that the transmission of professional knowledge is deeply aligned with cultivating morality and talent and the spirit of scientists.

3. Continuous Evolution Capability of Discipline Knowledge Updates: By dynamically mounting cutting-edge academic literature databases and discipline maps, the system ensures that teaching guidance keeps pace with the forefront of academia and the latest technologies in engineering and industry.

4. Intelligent Adaptability and High Integration of System Architecture: The system possesses full-stack integration capabilities that support intelligent agent orchestration, code interpreter, data chart generation, digital humans, and collaborative calls to external teaching Application Programming Interfaces (APIs).

2.2. Overall Research Paradigm Driven by "Personalized Education - Quality Assessment"

Introducing large-scale AI models can effectively combine the advantages of two major theories: on the one hand, large-scale models can refine teaching objectives into clear subject knowledge graphs and skill indicators, and establish regular data collection points throughout the teaching process to assist in evaluating the degree of teaching achievement; on the other hand, large-scale model-driven teaching intelligence agents can serve as learning tutoring scaffolds, providing heuristic dialogues, targeted resource recommendations, and practical guidance for graduate students at different starting points, thus providing operational technical support for individualized instruction.

This project establishes an overall research framework centered on a multimodal large-scale model, with theoretical models and system support evolving synergistically, and teaching and evaluation mutually empowering each other.

The overall logic is divided into three levels: First, constructing a multimodal data-driven theoretical model for personalized graduate education (Z-model), focusing on student-centered developmental adaptation; second, constructing an intelligent multidimensional teaching quality assessment model (K-model) covering three levels: basic course quality, teaching behavior, and interactive feedback, focusing on quality diagnosis on the teaching supply side; third, exploring the feature interaction and state feedback loop between the Z and K models, establishing a complementary coupling system and a five-layer support framework to provide a complete mechanism design for subsequent teaching practice.

3. Construction of a Theoretical Model for Personalized Education Based on a Multimodal Large Model

3.1. Multimodal learning data fusion perception and feature decoupling

To address the problem of distorted evaluation caused by traditional education relying solely on text assignments and grades, this model comprehensively integrates visual (student facial expressions, gaze focus, and posture), speech (pitch, acoustic energy, and speech rate/rhythm in classroom discussions), text (literature reading notes, in-class Q&A input, and paper drafts), and system interaction flow data (click streams, video fast-forward/pause, and dwell time). Through a multimodal feature fusion network, it decouples dynamic behavioral flows from static academic records in the time dimension, eliminating noise interference and accurately extracting the underlying latent vectors representing graduate students' cognitive load, learning focus, and inquiry motivation [9]. Figure 1 shows the architecture and adaptive recommendation pipeline of the AI large model-enabled postgraduate personalized education theoretical model (Z-Model).

3.2. Multi-dimensional Indicator Quantification System for Personalized Learning Paths

Based on the decoupling of multimodal features, the AI large model constructs in-depth quantitative indicators for graduate students' personalized learning paths from three dimensions: behavioral patterns, academic development trajectories, and research interests.

1. Behavioral Pattern Score (T_B): Collect student interaction sequence data B from smart classrooms, cloud platform discussion forums, and experimental platforms. Utilize a sequence clustering algorithm with attention mechanisms to extract learning behavioral patterns, measuring their intensity of independent exploration, collaborative tendency, and balance of time investment. Map this to a behavioral pattern health score $T_B \in [0,100]$.

2. Academic Progress Score (T_S): Track student performance sequences S in professional tests and task submissions at each week and stage. Introduce sliding time windows and temporal regression analysis to assess the growth rate and stability of knowledge acquisition, resulting in an academic progress score $T_S \in [0,100]$.

3. Interest Matching Score (T_I): Utilize large-scale model semantic embedding analysis to analyze students' multi-source interest vectors I from independent reading of

literature, elective topics, and experimental selections. Perform vector cosine similarity matching with the subject's cutting-edge knowledge tree and the tutor's research topic knowledge base to generate an interest-resource matching

score $T_I \in [0,100]$.

3.3. Quantification of Learning Progress and Mastery of Advanced Content Indicators

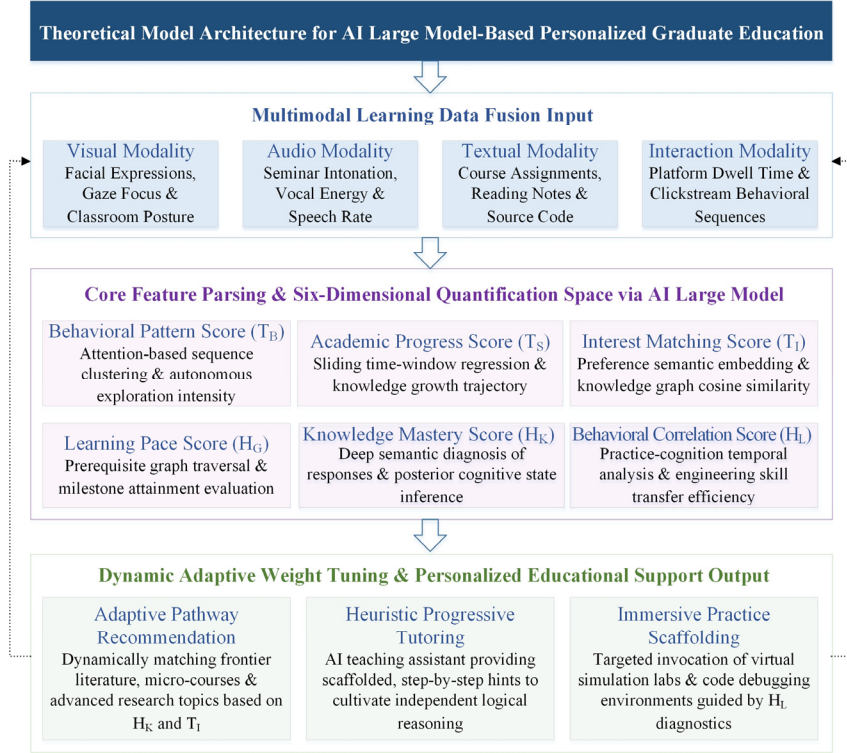


Fig 1. Architecture and adaptive recommendation flow of the theoretical model of personalized postgraduate education based on AI large model

Postgraduate training emphasizes scientific research and advanced practical skills; simply assessing memorization of knowledge points is no longer sufficient to reflect the true nature of the training. This model provides a fine-grained quantification of mastery of advanced content:

1. **Learning Progress Score (H_G):** Tracks the set of tasks completed by graduate students in the modular training program at each stage G . Combined with the predecessor and successor dependency graph of knowledge points, it assesses the macro-level progress achievement rate of their course study and scientific research training, quantifying it as a progress score $H_G \in [0,100]$.

2. **Knowledge Point Mastery Score (H_K):** Based on the educational big data model, it performs deep semantic judgment on students' objective evaluation answers, subjective derivation reports, and engineering code. Combined with cognitive diagnostic models (such as the DINA model or neurocognitive diagnostic network), it inversely infers the posterior probability of students' mastery at the underlying knowledge nodes, deriving the core knowledge point mastery score $H_K \in [0,100]$.

3. **Behavioral Association Mastery Score (H_L):** It conducts cross-correlation analysis between students' micro-operational behaviors (such as the step size of virtual simulation experiments, the number of code debugging and error correction rounds, and the depth of literature review) and their knowledge mastery level. Utilizing the multi-task reasoning ability of the big data model, it measures their actual skill conversion efficiency, generating a behavioral association mastery score $H_L \in [0,100]$.

3.4. Mathematical Expression and Adaptive Mechanism of Massive Personalized Education Theoretical Model

Based on the above six indicators, a large-scale personalized education theoretical model Z is constructed. The model defines the six feature vectors as the system input space, and its overall mathematical form is represented as a multivariate state tuple:

$$Z = \{T_B, T_S, T_I, H_G, H_K, H_L\} \quad (1)$$

To achieve dynamic adaptive guidance and personalized intervention for each student in large-scale teaching, the model constructs a comprehensive developmental efficacy evaluation function $\Phi(Z)$ based on state vectors, and dynamically adjusts it for different training stages through a variable weight matrix:

$$\Phi(Z) = \omega_1 \cdot T_B + \omega_2 \cdot T_S + \omega_3 \cdot T_I + \omega_4 \cdot H_G + \omega_5 \cdot H_K + \omega_6 \cdot H_L \quad (2)$$

The weight vector $W = (\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6)$ is not a subjectively fixed constant, but is dynamically and adaptively updated by the large-scale educational model based on the nature of the course (basic theoretical course, interdisciplinary cutting-edge seminar course, engineering practice training course) and the student's semester stage (course learning period, project initiation research period, and key project training period). Based on the comprehensive output of $\Phi(Z)$ and the weakness determination of each dimension in Z , the large-scale model adaptive recommendation engine automatically generates personalized high-level learning scaffolds for graduate students.

4. Construction of a Theoretical Model for Intelligent Multidimensional Teaching Quality Assessment

To completely overcome the shortcomings of previous teaching evaluation methods, such as "single indicators, reliance on subjective scoring, and superficiality," this study innovatively constructs an intelligent multidimensional teaching quality assessment theoretical model (K-model) covering three levels: "basic course quality, teaching behavior, and interactive feedback," focusing on a blended learning environment combining real classrooms and online learning. This model relies on a lightweight, seamless multi-channel audio and video acquisition system (such as a 30W edge computing multimedia analysis terminal) and a large-scale cloud-based analysis hub to support panoramic, routine, and continuous intelligent quantitative diagnosis of teachers' teaching status and students' responses. The three-layer indicator architecture of the AI large model-enabled intelligent multidimensional teaching quality evaluation model (K-Model) is illustrated in Figure 2.

4.1. Basic Course Quality and Quantification of Teaching Content (Course Quality Level)

The quality of basic lessons is the foundation of classroom

teaching quality, mainly examining the standardization of the teaching plan, the richness of the teaching content, and the consistency between the blackboard writing and the lesson plan.

1. Blackboard Writing Standardization and Font Score (F_D): Images D of the blackboard or electronic whiteboard are captured using a dedicated blackboard camera. A large-scale visual algorithm extracts the stroke trajectories, layout structure, and text standardization of the writing. Semantic and layout similarity are compared with a standard knowledge set to output a blackboard writing quality score F_D .

2. Lesson Plan Content Completeness Score F_P : The digital lesson plans and courseware P submitted by teachers are fully analyzed. A large-scale model evaluates the clarity of teaching objectives, the integration of cutting-edge academic knowledge, the logic of analyzing key points and difficulties, and the integration of ideological and political elements into the course, generating a lesson plan content score F_P .

3. Abstract Semantic Difference Score F_{CD} : Utilizing the automatic summarization and semantic understanding capabilities of large models (such as DeepSeek), a dynamic summary D_{abs} is extracted from the core content of the classroom blackboard/PPT, and a summary of the core points of the lesson plan C_{abs} is extracted simultaneously. The deviation distance between the two

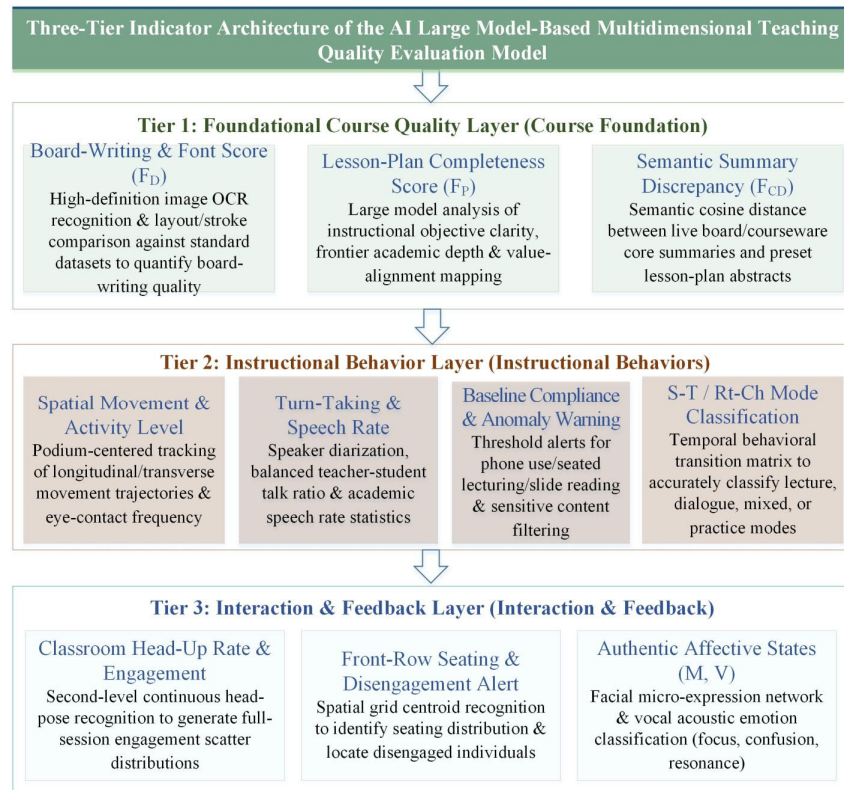


Fig 2. Three-layer indicator architecture of the intelligent multidimensional teaching quality assessment model (K model) based on AI large model

is calculated using a deep semantic similarity function:

$$F_{CD} = 1 - \text{CosineSimilarity}(\text{Emb}(D_{abs}), \text{Emb}(C_{abs}))$$

If F_{CD} is abnormally high, it suggests that the teacher has seriously deviated from the teaching syllabus or reduced the content; if it is within a moderate range, it reflects that the teacher has made good extensions and developments based on the classroom learning situation;

4. Teaching progress achievement analysis: The big model

automatically performs semantic segmentation and concept localization on the speech-to-text transcripts of each teacher's lecture, matches them with the preset teaching calendar, and automatically determines the achievement of the teaching objectives for each lesson.

4.2. Quantification of Teachers' Teaching Behaviors and Temporal Characteristics (Behavioral Level)

Teaching behavior directly reflects a teacher's teaching art and professional demeanor. The large-scale model system calculates a teacher's posture, spatial movement trajectory, speech rate, and teaching mode in real time.

1. Teacher Activity and Movement Analysis: Using the podium as the origin, a multi-target tracking algorithm is used to analyze the frequency of teachers' lateral movement, vertical patrols of the seating area, and eye contact with students, constructing a comprehensive activity index to break the passive and dull situation of "teachers sticking to the podium and reading slides".

2. Lecture Ratio and Interaction Rounds: Through high-precision microphone arrays and speaker separation technology, the ratio of teacher lecture time to student discussion time is statistically analyzed (the ideal teacher-student speaking ratio in high-level graduate seminars tends to be 50/50), and the frequency of speech rounds in teacher-student Q&A is recorded.

3. Lecture Pace and Acoustic Appeal: The speech recognition engine analyzes the teacher's lecture pace (words/minute) in real time to assess whether it is at a moderate academic communication pace, and combines the intonation fluctuation to evaluate the appeal of the lecture.

4. Intelligent monitoring and early warning of abnormal classroom behavior: The system automatically sets the warning threshold for teaching bottom lines, and instantly and imperceptibly identifies behaviors such as teachers being late or leaving early, answering or making phone calls during class, sitting and lecturing for extended periods (>15 minutes), reading PPTs with their heads down for extended periods (>15 minutes), and playing video recordings one-way for extended periods (>15 minutes), triggering compliance prompts in the background; at the same time, the large model establishes a negative interception and weight deduction mechanism for politically sensitive content involving ideology and uncivilized language.

5. Intelligent judgment of ST model and Rt-Ch teaching mode: Based on the time-series transition matrix of student behavior and teacher behavior, the system automatically calculates the teacher-student behavior conversion rate C_h and the student behavior occupancy rate R_t , accurately dividing the classroom into "lecture-type, dialogue-type, blended, and practice-type", and guiding graduate seminars to evolve towards the higher-level "dialogue-type and blended" modes.

4.3. Interactive Feedback and Quantification of Teachers' and Students' Genuine Emotions (Feedback Level)

The core focus of postgraduate teaching effectiveness lies in whether students engage in higher-order cognitive processes and experience emotional resonance. The assessment model delves into subtle classroom feedback through multimodal perception.

1. Classroom Head-Up Rate and Attention Scattered Distribution: Continuously analyzes the percentage of students looking up at the blackboard/teacher within seconds, generating a "Head-Up Rate - Time" fluctuation curve for the entire class; combines this with the frequency of student head movements to calculate the average activity level,

constructing a "Classroom Attraction Scattered Model" to intuitively depict students' focus during explanations of challenging knowledge points.

2. Front Row Seating Rate and Participation: Using the classroom's depth coordinates as the axis, automatically calculates the forward clustering trend of student seating, and sets threshold warnings for individuals who are constantly looking down and detached from teaching interaction.

3. Set of Real Facial Emotions of Teachers and Students (M): Through a facial micro-expression recognition network, extracts facial features of teachers and students during key discussion sessions, classifying them into a set of real facial emotional states $M = \{M_1, M_2, \dots, M_m\}$ (such as focus, insight, doubt, fatigue, frustration, etc.), accurately capturing deep-seated academic confusion.

4. The set of genuine emotional states in the voice (V): The acoustic characteristics (fundamental frequency, formants, energy envelope) of teachers and students during communication and questioning are classified into emotional states to generate a set of genuine emotional states in the voice $V = \{V_1, V_2, \dots, V_m\}$ (such as confidence, hesitation, excitement, low mood, etc.), which comprehensively reflects the depth of the intellectual exchange and academic atmosphere in the classroom academic discussion.

4.4. Mathematical Expression and Dynamic Comprehensive Weighting of the Multidimensional Teaching Quality Assessment Theoretical Model

Integrating the quantitative characteristics of the above three levels, the core mathematical expression of the intelligent multidimensional teaching quality assessment theoretical model K is established as follows:

$$K = \{F_D, F_P, F_{CD}, M, V\} \quad (3)$$

To provide a scientific and objective comprehensive evaluation score for classroom quality $\Psi(K)$, the model introduces a combined weighting algorithm based on the coefficient of variation and expert prior knowledge, defining the comprehensive evaluation mapping relationship:

$$\Psi(K) = \alpha_1 \cdot F_D + \alpha_2 \cdot F_P + \alpha_3 \cdot (1 - F_{CD}) + \beta_1 \cdot f_{att}(M) + \beta_2 \cdot g_{aff}(V) \quad (4)$$

Where $f_{att}(M)$ and $g_{aff}(V)$ represent the positive score functions of emotion and focus after nonlinear attention-weighted aggregation of the facial expression set M and the vocal emotion set V through a multimodal large model; α_i and β_j are normalized weight coefficients, satisfying $\sum \alpha_i + \sum \beta_j = 1$. The K model completely changes the traditional extensive evaluation paradigm of "one-time form filling at the end of the semester" and supports the generation of accompanying teaching evaluation profiles that include "classroom data briefings, indicator radar charts, abnormal problem lists, and reverse-generated knowledge maps".

5. The Two-Way Coupling Mechanism and Multi-Level Support Framework for Personalized Education and Teaching Quality Assessment

5.1. The Efficient Two-Way Coupling Mechanism between Personalized Education and Teaching Quality Assessment

Figure 3 shows the bidirectional dynamic coupling mechanism between postgraduate personalized education (Z) and teaching quality evaluation (K). In the traditional education system, "learning" and "assessment" often become two parallel lines that never intersect. This project delves into the similarities and complementarities between the personalized education theoretical model Z and the multidimensional assessment theoretical model K in terms of data sources, algorithmic characteristics, and educational goals, establishing a two-way dynamic coupling mechanism that refines and promotes synergistic interaction.

1. The feedback mechanism of quality assessment driving personalized education ($K \rightarrow Z$): Fine-grained data collected by the K model in the classroom (such as the overall facial confusion level M of students when deriving a certain formula, low levels of interaction activity, and semantic

deviation of the summary F_{CD}) is injected into the Z model in real time. Based on this, the Z model dynamically calibrates the learning progress score H_G and the knowledge point mastery score H_K , automatically lowers the conceptual threshold of subsequent resource pushes, and intelligently matches tiered and progressive micro-lesson cases for the group, realizing "learning based on assessment and policy implementation based on assessment".

2. The reverse calibration mechanism of personalized education for quality assessment ($Z \rightarrow K$): The student individual profiles accumulated by the Z model over a long period of time (such as prior knowledge background, cognitive style, and interest characteristics T_1) are inversely mapped to the assessment weight adjustment matrix of the K model. For example, if the student group in a class generally has a "code-based" learning style, the K model will automatically increase the weight of hands-on interaction and problem-solving behavior and decrease the weight of blackboard writing when evaluating the class. This avoids the rigid evaluation drawbacks of "measuring a wide variety of classes with a single standard" and achieves "evaluation based on learning and working in the same direction".

3. Efficient data filtering and retention in the system: To address the challenges of large amounts of classroom audio and video stream data and high computational costs, the coupling

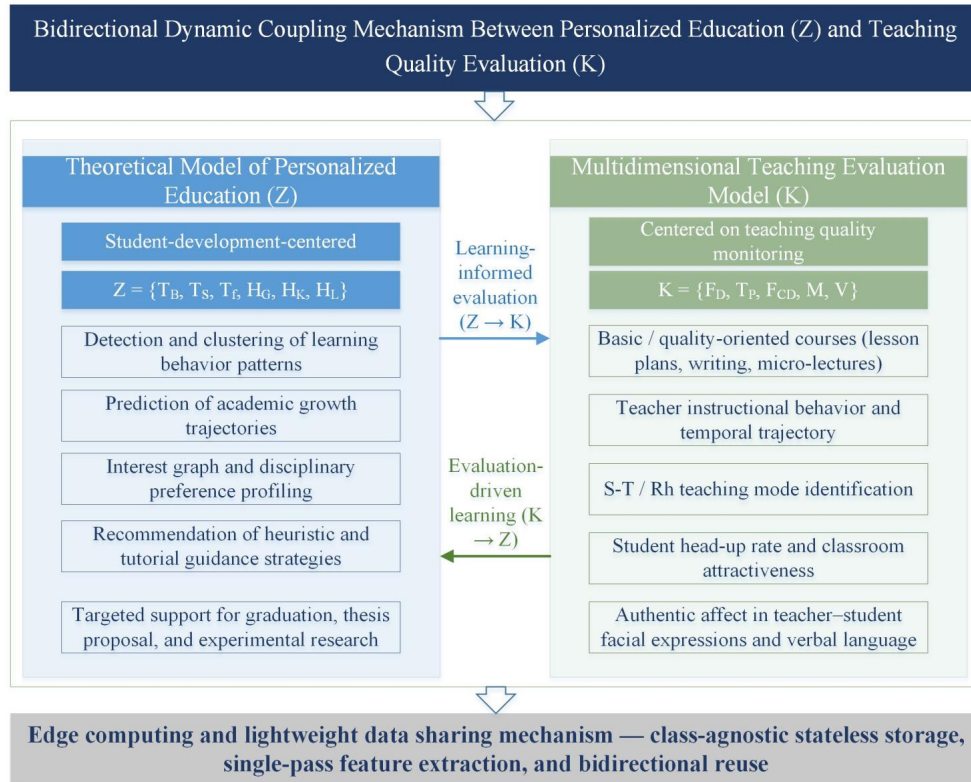


Fig 3. Two-way dynamic coupling mechanism between personalized education (Z) and teaching quality assessment (K) for graduate students

mechanism adopts a "lightweight edge extraction - core semantic sharing" strategy. This ensures that the underlying computational costs of face recognition and speech transcription are executed only once. The extracted feature vectors serve both individual learning modeling and whole-class classroom quality evaluation, greatly reducing system redundancy and improving computational throughput.

5.2. Five-layer, Multi-level Teaching Support System Architecture Design

To support the engineering implementation of the Z-model, K-model, and their bidirectional coupling mechanism in a university environment, this study designed a hierarchical, highly cohesive, and loosely coupled "five-layer teaching support system architecture":

1. Cloud Service Layer: Provides foundational computing resources and infrastructure services. This includes domestically developed AI chip clusters (GPU/NPU), a distributed model fine-tuning environment, a massive digital education resource asset management pool, cross-school online teaching collaboration channels, and a secure content distribution network, ensuring high availability and data compliance for large-scale model inference and training.

2. AI Foundation Model Layer: Serves as the core intelligent hub. Deploys a general-purpose large-scale model foundation with multimodal processing capabilities (supporting joint embedding of text, vision, and audio), performs SFT fine-tuning using educational-specific datasets, and is equipped with external subject knowledge graphs and vector databases (RAG architecture) to eliminate academic illusions and achieve deep logical reasoning and high-quality content generation.

3. AI Function Service Layer: Encapsulates and exposes core intelligent capability components, mainly including four functional modules: intelligent evaluation module, personalized analysis module, content generation module, and multimodal interaction module.

4. Data Processing Layer: Constructs a multi-source data governance channel that spans the entire lifecycle. The system includes a "Dynamic Data Acquisition Module" for real-time collection of classroom audio and video streams, a "Static Data Integration Module" for compiling historical grades and curriculum plans, and a "Privacy Data Processing Module" based on differential privacy, federated learning, and national cryptographic encryption technologies to ensure the absolute security and autonomous control of students' portraits, voiceprints, and academic records.

5. Platform & System Layer: Business interaction interfaces and application platforms for different stakeholders. It unifies and integrates the academic affairs management system, teaching supervision and evaluation system, teacher in-class reflection workbench, student adaptive learning space, and virtual teaching and research office collaborative tools to form a unified digital and intelligent teaching portal for the entire school.

5.3. Design of Multi-Agent Cooperative Mechanism

Above the AI-driven functional service layer, this system constructs a teaching mechanism based on multi-agent collaboration, forming a division of labor among three core intelligent agent roles:

1. "Digital Intelligent Teaching Assistant" (Teacher-Agent): Assists teachers in conducting pre-class learning assessments and lesson plan generation, providing real-time alerts for classroom anomalies and student confusion based on K-model feedback during class, and automatically generating learning summaries and reflection/improvement suggestions after class. This frees teachers from repetitive tasks, allowing them to focus entirely on teaching and mentoring.

2. "Digital Intelligent Learning Assistant" (Tutor-Agent): Tailor-made one-on-one private tutoring for graduate students. Based on Z-model dynamic programming learning paths, it employs a gradient interaction strategy of "inspirational guidance rather than direct answers" when graduate students are engaged in programming debugging, formula derivation, and experimental design, cultivating students' independent thinking abilities.

3. "Digital Intelligent Partner" (Peer-Agent): Acts as a

"virtual fellow student/discussion partner." During graduate students' academic discussions and research projects, the digital intelligent partner can participate in dialogue through debates, questioning of solutions, or supplementation of the latest international literature, effectively stimulating students' critical academic thinking and interdisciplinary inspiration.

6. Design of Implementation Path and Mechanism for Postgraduate Education Based on AI Large Model

Postgraduate education aims to cultivate top-notch talents with independent scientific research and innovation capabilities as well as advanced and complex engineering practice abilities. Transforming the aforementioned AI-based Z-model, K-model, and their five-layer teaching support system into practical and feasible educational practices requires establishing a rigorous and scientific implementation path and a multi-dimensional mechanism for assurance. This research, targeting the characteristics of high-level postgraduate talent cultivation, systematically constructs a three-pronged mechanism guarantee system focusing on the construction of physical and digital environments, the enhancement of human-machine collaboration capabilities within the mentor team, and data ethics and security regulations.

6.1. Construction Path of Integrated Hardware and Software Digital Teaching Environment

1. Construction of a routine multimodal perception classroom environment empowered by edge computing: Low-power edge intelligent multimedia processing terminals are planned and deployed in classrooms, establishing a time-synchronized audio and video data stream pipeline through whiteboard cameras, student panoramic cameras, and multi-channel directional audio arrays. While ensuring real-time local data slicing and anonymization, it supports low-latency extraction of classroom behavior features and ST time-series model parsing, providing stable and efficient data input for the K-model.

2. Construction of subject-specific knowledge graphs and vector resource pools: Relying on key university disciplines and first-class course resources, a high-dimensional subject knowledge graph integrating textbook outlines, academic monographs, high-level journal articles, and engineering standards and specifications is constructed. Retrieval-enhanced generation (RAG) technology is used on the large model base to ensure that the intelligent agent possesses a high degree of professionalism, accuracy, and rigor in heuristic guidance and academic question-and-answer processes.

3. Deployment of a cloud-integrated collaborative interactive service platform: A unified portal is constructed that connects the academic affairs system, supervision system, and personalized learning spaces, achieving seamless integration between student-side adaptive guidance terminals and teacher-side in-class teaching reflection workbench.

6.2. Mechanism for Enhancing the Human-Computer Collaborative Competency of Mentor Teams and Instructors

1. Digital Transformation and Repositioning of the

Teacher's Role: Guiding graduate instructors and mentors to shift from traditional "single knowledge transmitters and experience evaluators" to "organizers of human-machine collaborative discussions, high-level research guides, and facilitators of critical thinking." Teachers should be adept at using the multi-dimensional classroom assessment radar charts and anomaly warning lists generated by the K-model to conduct evidence-based teaching reflection and continuous optimization of curriculum design;

2. Training on Large-Scale Model Prompt Engineering and Teaching Intelligent Agent Arrangement Capabilities: Establishing a regular virtual teaching and research room training mechanism, systematically conducting specialized training on large-scale model prompt word design, educational intelligent agent workflow arrangement, and multimodal learning data interpretation, effectively enhancing the mentor team's high-level competence in using generative artificial intelligence technology to conduct personalized inspirational guidance.

3. Design of a Closed-Loop Operation System for Continuous Quality Improvement (CQI): Establishing and improving teaching quality assurance regulations based on "data collection - intelligent diagnosis - targeted push - teacher reflection - continuous tracking," using the accompanying evaluation results of the large-scale model as an important reference for teacher teaching development and curriculum construction, promoting a spiral improvement in teaching quality.

6.3. Data Privacy and Security, Academic Ethics and Algorithm Supervision and Protection Mechanisms

1. Strict Student Privacy Data Security Protection Mechanism: Strictly adhering to the "Personal Information Protection Law" and the "Cybersecurity Law," the system rigorously enforces informed consent before collecting students' facial features and voice data. Differential privacy injection and local edge computing desensitization technologies are comprehensively introduced at the underlying data processing layer. All biometric sensitive data is instantly abstracted into behavioral vectors at the classroom edge node, prohibiting the uploading of students' original portraits and voiceprint information to the public network.

2. Robust Algorithm Content Security and Ideological Defense: In accordance with the "Interim Measures for the Management of Generative Artificial Intelligence Services," a multi-level sensitive word filtering, adversarial attack protection, and moral education value alignment review mechanism are established for the output of large models to resolutely prevent the generation of academic misconduct, value bias, or misleading content.

3. Establishment of Red Lines for Academic Integrity and Prevention of Technology Abuse: Clear behavioral guidelines are established for graduate students using AI large models for scientific research and course learning. Large models are positioned as "auxiliary inspirational tools and partners for intellectual exchange," resolutely preventing students from using large models for academic misconduct such as paper writing, data fabrication, or research fraud. A traceability and integrity review mechanism for AI-generated text is established to ensure that technology is used for good and academic rigor is maintained.

7. Conclusion and Future Outlook

This paper addresses the deep-seated contradiction between "large-scale training and personalized development of top-notch innovative talents" in postgraduate education in the new era. Relying on a large-scale AI education model and multimodal technology, it systematically constructs theoretical models, designs mechanisms, and plans application frameworks. Key research findings include: First, a multimodal data-driven large-scale personalized education theoretical model (Z-model) is constructed, revealing quantitative methods for learning paths and mastery indicators; second, an intelligent multidimensional teaching quality assessment theoretical model (K-model) covering three levels—basic course quality, teaching behavior, and interactive feedback—is constructed, achieving multidimensional quantitative representation of classroom teaching status; third, the bidirectional dynamic coupling mechanism between the Z-model and the K-model is systematically clarified, and a cloud-integrated five-layer, multi-level teaching support system architecture is proposed; fourth, an implementation path and institutional guarantee mechanism for advanced training are designed in depth.

The theoretical model and mechanism design proposed in this study provide a novel theoretical framework and implementation path for effectively overcoming the limitations of traditional postgraduate education evaluation, such as its single evaluation dimension, lagging process feedback, and insufficient personalized support. Future research will closely align with the national "Artificial Intelligence+" strategy, conducting further in-depth explorations in areas such as the development of embodied intelligent virtual mentors, the construction of cross-university secure federated knowledge networks, and the ethical guidelines for large-scale educational model algorithms, providing solid support for promoting the digital transformation of higher education and the high-quality development of postgraduate education.

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References

- [1] Wang, X., & Long, Q. P. (2025). Empowering the cultivation of innovative ability for MPA postgraduates through education-specific large models. *Journal of Higher Education*, 11(31), 5–10,15.
- [2] Zhang, J. J., & Tao, X. (2026). Reconstruction of supervisor-postgraduate relationship in the era of artificial intelligence. *Modern Education Science*, (2), 121–128.
- [3] Huang, X. (2026). AI-enabled digital transformation of higher engineering education: A theoretical framework of "strategy-path-guarantee". *Science & Education Journal*, (9), 20–25.
- [4] Cao, P. J., Xie, Y. B., Wu, H. Z., et al. (2024). Development status, innovative architecture and application prospect of

- educational large models. *Modern Educational Technology*, 34(2), 5–12.
- [5] Liu, B. Q., Yu, Y. K., Wang, T., et al. (2024). Artificial intelligence educational large models: System architecture and key technical strategies. *Open Education Research*, 30(5), 76–86.
- [6] Qiao, X. Q., Wang, N., Gao, P. P., et al. (2024). Large models facilitating the digital transformation of higher education and the cultivation of top-notch innovative talents: Exploration and practice of Beijing University of Posts and Telecommunications. *China Information Technology in Education*, 30(9), 9–17.
- [7] Wu, Y. H., Yan, H., & Ma, X. L. (2024). Development of the standard system framework for general artificial intelligence educational large models. *Modern Educational Technology*, 34(4), 28–36.
- [8] Lu, Y., Yu, J. L., & Chen, P. H. (2024). Research on the construction and application of teaching agents based on large models. *China Educational Technology*, (7), 99–108.
- [9] Xu, S. Q. (2021). Research on online teaching quality evaluation in universities based on deep learning networks. *Information Technology*, (7), 9–14.